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Analysis of Multi-Criteria Fire Detection Data and Early Warning Fire Detection Prototype Selection

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13. ABSTRACT (*Maximum 200 words*)

This report describes the analysis of Fire/Nuisance Source data and the selection of sensors for an early warning, multi-criteria, fire detection system for the Office of Naval Research (ONR) program on Damage Control: Automation for Reduced Manning (DC-ARM). In this work, the analysis of transient fire signatures is studied using a probabilistic neural network (PNN). Experiments are described to study the effects of various PNN training parameters and to determine the optimal sensor suite combination, which enables both early fire detection and high nuisance source rejection. Comparisons are made between the candidate sensor arrays, commercial fire detection systems, and sensor arrays proposed in previous reports. Recommendations and directions for future research are also given.

14. SUBJECT TERMS

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ANALYSIS OF MULTI-CRITERIA FIRE DETECTION SYSTEM DATA AND EARLY WARNING FIRE DETECTION PROTOTYPE SELECTION

1. INTRODUCTION

A series of tests were conducted to evaluate sensors for an early warning fire detection system under development. The tests were conducted from August 30-September 3, 1999 onboard the ex-USS SHADWELL, the Naval Research laboratory's full scale fire research facility in Mobile, Alabama (reference (a)). The tests have been used to evaluate and improve the multivariate data analysis methods and candidate sensor suites described in references (b-d). The objective of the program is to develop an improved early warning fire detection system that will provide early fire detection with a low false alarm rate.

2. BACKGROUND

The system under development combines a multi-criteria (sensor array) approach with sophisticated data analysis methods. Together an array of sensors and a multivariate classification algorithm produce early fire detection with a low false alarm rate. Several sensors measuring different parameters of the environment produce a pattern or response fingerprint for an event. Multivariate data analysis methods are trained to recognize the pattern of an important event such as a fire. Multivariate methods are trained using data in a training set and the training set consists of sensor responses to events and nonevents under various conditions. The data sets used for sensor array evaluation require that the sensors be in close proximity so that it can be assumed that the sensors are observing the same test atmosphere.

Multivariate classification methods rely on the comparison of events with nonevents. Variations in the response of sensors can be used to train an algorithm to recognize events when they occur. A key to the success of these methods is the appropriate design of sensor arrays and the training sets used to develop the algorithm. Although, the event is most important, it is critical that the algorithms recognize nonevents as well.

Standard test procedures included a baseline response to establish initial sensor conditions, exposure test, and recovery back to baseline. For example, a typical test collected 10 minutes of ambient air, followed by an exposure to a fire for 20 minutes, then re-exposure to ambient conditions for 10 minutes. Chemical sensors are subject to noise and other fluctuations with time. Therefore, typical sensor performance or typical baseline responses over the test period were determined by exposing the sensors to ambient air for the entire test period. Baseline

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tests conducted at different times of the day can be used to determine environmental effects and how they influence the sensors.

Data were collected by the multi-criteria fire detection system on the ex-USS SHADWELL. These data were used to validate the performance of the system with respect to the laboratory database (ref (b)) and to optimize the sensor array selection for prediction. This report describes:

(1) The evaluation of the candidate suites and the probabilistic neural networks for early and reliable detection of several types of fires (i.e., validation database);
(2) The database that was used to improve the classifier for shipboard use (i.e., use the database as a secondary training set if the validation is not satisfactory); and
(3) The reliability of the multi-sensor detection system with respect to nuisance alarms.

The detection system was installed in the forward area of the ship on the second deck FR 15-22 as shown in Figure 1 along with selected SHADWELL sensors including thermocouples and continuous oxygen (O_2), carbon monoxide (CO) and carbon dioxide (CO_2) gas sampling. The SHADWELL sensors were used to verify the detection system. The location of the fire is also shown in Figure 1. The standard test procedure was used and included 10 minutes of ambient background air, followed by an exposure to a fire for a fixed finite time (20 minutes), and then re-exposure to ambient conditions (10 minutes). Background tests were conducted by exposing the sensors to the ambient condition for the entire test period (40 minutes). After every 2 fire tests, a nuisance source test was conducted, so that the fire and nuisance tests were intermixed. References (e and f) describe the field test parameters and the results.

The sensors were calibrated prior to installation with calibration gas mixtures diluted to an appropriate level using clean breathing air (upper limit of sensor range). The calibration of the sensors was verified daily, while the sensors were mounted in place.

3. FIRE SCENARIOS

A total of 30 tests were conducted to evaluate the detection system. Fire scenarios used common shipboard combustibles, such as oily rags, cardboard, paper, sheets, and mattresses as the fuel. Nuisance source scenarios represented common shipboard activities, such as welding, cutting steel with a torch, toasting, smoking, cleaning, personal products, and burning popcorn. The majority of the sources were located at 2-17-0. Table 1 summarizes the fire/nuisance source scenarios and other general test conditions for each test. Replicates were not tested sequentially. The small heptane pan fire was used as our standard test and was used periodically to determine the reproducibility and the stability of the sensors during the test series.

Table 2 presents a list of the sensors used in the test program. Under the column labeled species, the parenthetical term represents the sensor name used throughout this program. The majority of the gas sensors were electrochemical cell technology, except as noted below. These sensors were used because they provided a means to economically measure many

species. Past experience with the CO sensors indicated that these sensors are accurate at low ppm concentrations, are easy to operate and calibrate and are reliable over repetitive testing. The general hydrocarbon sensor (calibrated with ethylene) was a solid state metal oxide sensor. The CO_2 meter was designed for indoor air quality measurements based on non-dispersive infrared (NDIR) technology. All of the gas sensors operated via gas diffusion to the unit.

At the beginning of each day, the daily checklist was completed. Prior to each test, the fire area was cleared of all personnel not involved with testing. All hatches and doors were closed. Ventilation to the space remained off for the first 30 minutes of the test. After completion of these tasks, test personnel were positioned in the appropriate locations. When the fuel package was ready and the safety team was in position, data collection and videos were initiated to commence the test. Following approximately 10 minutes of background data, the source was initiated. For the smoldering fire scenarios, the soldering irons were energized. Event data were collected for 20 minutes. After the event was secured, and during compartment venting, the data collection continued for 10 additional minutes to assess the recovery of the sensors following an event. Once the Safety Team had deemed the test area safe for personnel without breathing protection, the test area was prepared for the next test. This preparation included any cleanup of the test area, equipment setup for the next test, and verification of instruments.

All of the sensor responses were collected using the MASSCOMP on the SHADWELL.

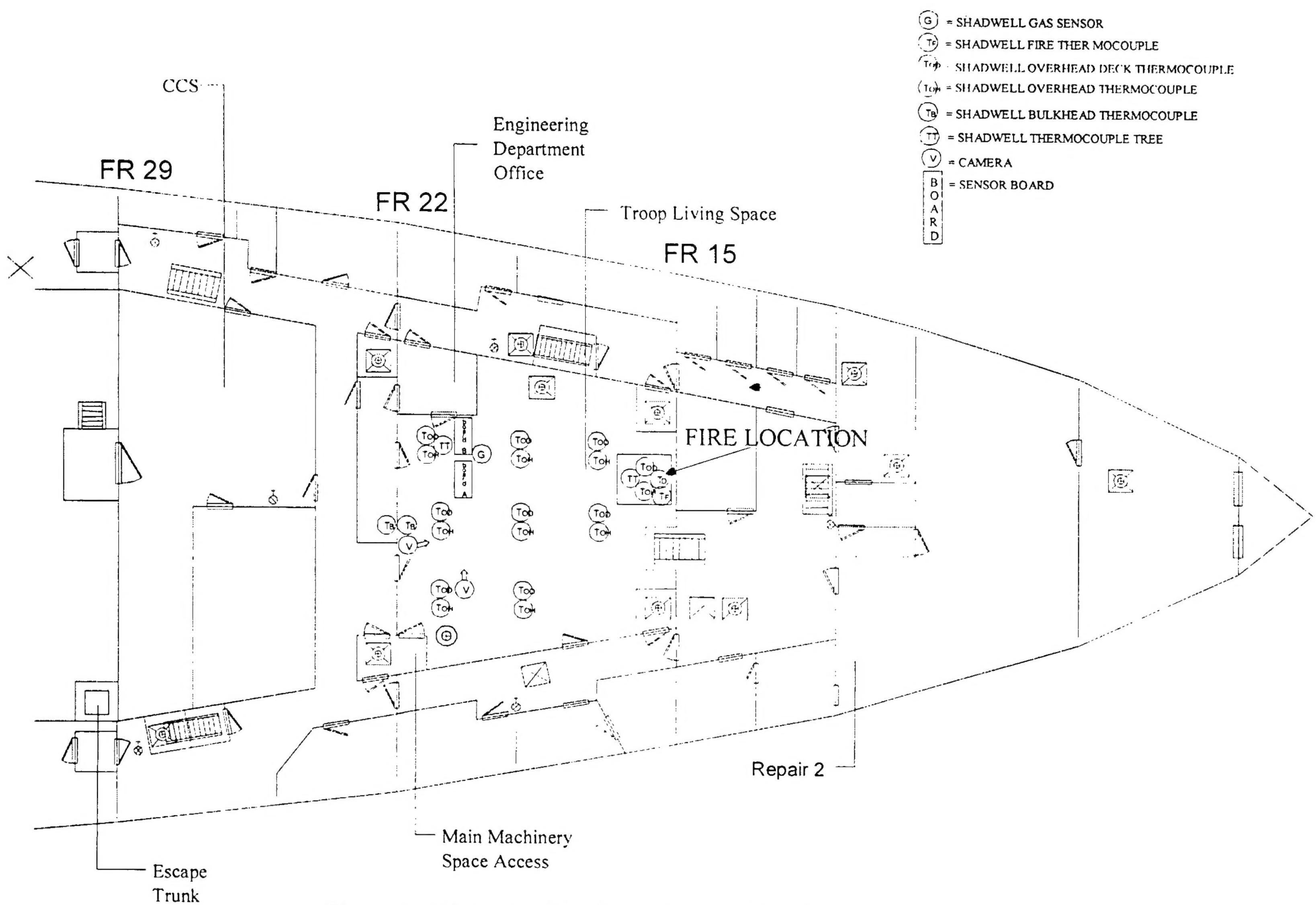

Figure 1. Diagram of the forward area of the ship on the second deck between FR 15-22 showing the sensor and fire locations.

Table 1. Summary of Test Scenarios

TEST	FIRE SCENARIO	COMMENTS
MV-00	Background	
MV-01	Flaming heptane in 15 cm (6.0 in.) diameter pan.	Approximately 100 ml (3.5 fl. oz.) heptane in pan, **Standard Test**
MV-02	Flaming heptane in 15 cm (6.0 in.) diameter pan.	Repeat MV-01, **Standard Test**
MV-03	Background	Repeat MV-00
MV-04	Flaming heptane in 15 cm (6.0 in.) diameter pan.	Repeat MV-01, **Standard Test**
MV-05	Flaming oily rags in small trash can	0.1 m^2 (1 ft^2) rags saturated with 118 ml (4 oz.) 10W30 motor oil, ignited with a butane lighter
MV-06	Burning Toast	4 slices of bread in a toaster locked on
MV-07	Flaming paper and cardboard in small trash can	5 sheets of newspaper and 0.3 m^2 (3 ft^2) of cardboard, ignited with a butane lighter
MV-08	Smoldering oily rags in small trash can	0.1 m^2 (1 ft^2) rags saturated with 118 ml (4 oz.) 10W30 motor oil, ignited with a butane lighter
MV-09	Burning Popcorn	1 bag of popcorn in microwave for 12 minutes
MV-10	Flaming oily rags in small trash can	Repeat of MV-05
MV-11	Flaming paper and cardboard in small trash can	Repeat of MV-07
MV-12	Welding	
MV-13	Background	Repeat MV-00
MV-14	Smoldering paper in small trash can	5 sheets of newspaper and 0.3 m^2 (3 ft^2) of cardboard, ignited with a butane lighter
MV-15	Smoldering cotton sheet, pillow, wool blanket, and mattress	Fuel package heated with a 300 W heating coil energized to 54 V. Coil on top center under its own weight.
MV-16	Cutting Steel with an Acetylene Torch	
MV-17	Flaming fuel oil in 0.3 m x 0.3 m (1 ft x 1 ft) square pan	1.1 liters (0.3 gal) F-76 with ethyl alcohol accelerant
MV-18	Flaming 0.3 m x 0.3 m x 0.2 m (1 ft x 1 ft x 10 in.) wood crib	Crib constructed with 4 rows of 4 – 51 mm x 51 mm x 0.2 m sticks. Crib ignited with a small heptane pan fire
MV-19	Cleaning Supplies	
MV-20	Smoldering pillow in a pillow case, 15.2 cm x 15.2 cm (6 in. x 6 in.)	Fuel package heated with a 300 W heating coil energized to 54 V. Coil on top center under its own weight.
MV-21`	Flaming heptane in 15 cm (6.0 in.) diameter pan.	MV-01, **Standard Test**
MV-22	Cigarette Smoke	
MV-23	TODCO Wall Board exposed to a flame	TODCO wallboard, 10 cm x 30 cm (4 in. x 1 ft.) exposed to a flame
MV-24	Pipe Insulation exposed to flame	Calcium silicate insulation with glass cloth lagging, painted (45 cm) exposed to a flame
MV-25	Personal care products	Rubbing alcohol, Ben-Gay, shaving cream, and Tinactin
MV-26	Background	Repeat MV-00
MV-27	Smoldering cotton sheet, pillow, wool blanket, and mattress	Repeat MV-15
MV-28	Smoldering cables in overhead cable rack	LSDSGU-14 cable (33 cm) ohmically heated with a 600 A arc welder
MV-29	Background	Repeat MV-00

Table 2. Sensors for Multi-criteria Detection Tests

No.	Species	Sensor Range	Resolution	Model No.	Manufacturer
1	Oxygen (O_2)	0-25%	0.1% O_2	6C	City Technology
2	Carbon monoxide ($CO_{20000\ ppm}$)	0-20000 ppm	5 ppm		City Technology
3	Carbon monoxide w/ H_2 compensation ($CO_{4000\ ppm}$)	0-4000 ppm	1 ppm	A3ME/F	City Technology
4	Carbon monoxide ($CO_{50\ ppm}$)	0-50 ppm	0.5 ppm	TB7E-1A	City Technology
5	Carbon dioxide (CO_2)	0-5000 ppm	Accuracy= greater of $\pm$5% of reading or $\pm$100 ppm	2001V	Telaire/Englehard
6	C_1 to C_6 (ETHYL) Hydrocarbons (will be calibrated with ethylene)	0-50 ppm	$\pm$2.5 ppm	SM95-S2 with general hydrocarbons solid state sensor	International Sensor Technology
7	C_1 to C_6 (ETHYL) Hydrocarbons	0-20000 ppm			
8	Nitric oxide (NO)	0-20 ppm	0.5 ppm	TF3C-1A	City Technology
9	Hydrogen chloride (HCl)	0-10 ppm	0.5 ppm	TL1B-1A	City Technology
10	Temperature (Thermocouple or TC)	-200 to 1250EC	1EC or 0.75%	Type K, 0.127 mm bare bead TC	Omega
11	Temperature (Temp Omega)	-20EC to 75EC	$\pm$0.6EC accuracy	HX93 transmitter (RTD)	Omega
12	Relative humidity (RH)	3-95%	$\pm$2% RH accuracy	HX93 transmitter	Omega
13	Hydrogen Sulfide (H_2S)				City Technology
14	Photoelectric smoke detector (PHOTO)	0 - 19% Obs/m		4098-9701	Simplex
15	Ionization smoke detector (ION)	1.6 -10% Obs/m		4098-9716	Simplex
16	Residential ionization smoke detector (RION)			83R	First Alert
17	Optical Density Meter (ODM) (1 m path length)			Infrared light emitting diode and receptor	Meredith
18	Optical Density Meter (ODM) (1 m path length)			Laser and Photodiode	Motorola
19	Optical Density Meter (ODM) (1 m path length)			White Light	

4. DATA ANALYSIS

The data were received in two forms: raw and processed. The raw data were taken directly off the MASSCOMP. The processed data included engineering units, and the Optical Density Meter (ODM) and Simplex smoke detectors (PHOTO and ION) were in percent obscuration per meter (% obs/m) as described in reference (b). The first minute of background was used for the initial intensity I_0 in the % obs/m calculation. The data from the Simplex sensors were collected every four to five seconds, while all the other sensors provided data every second. For pattern recognition, all of the data responses were consolidated into a data matrix containing all the sensor responses. Therefore, only the responses occurring at the same time as the Simplex sensors were included in the data matrix. The data sets were examined directly to determine the best parameters for shipboard detection. In addition, these tests were used as a prediction set to validate the algorithms developed using the laboratory data sets described in references (b-d). For this application, strong nuisance source rejection was given the highest consideration.

The data were analyzed on a PC using routines written in MATLAB, version 5.2 (Mathworks, Inc., Natick, MA). Many of the routines were implemented using the PLS_toolbox, version 2.0c (Eigenvector Technologies, Inc., Manson, WA). All the matrices were autoscaled (column mean of zero, unit variance). The classifier used in this study was a Probabilistic Neural Network (PNN) (reference (g)) that was developed at the Naval Research laboratory for chemical sensor arrays. A graphical user interface (GUI) for use with MATLAB entitled MATLAB Graphical Interface for Classification Algorithms (MAGICAL) was developed for easier implementation of PNN routines. The software has the capability to run the PNN in cross-validation and venetian blinds (VB) mode (random selection of training and prediction sets from a single data set). The GUI has functionality that enables data visualization, manual and automated variable selection, sigma calculation and optimization, results plotting (PNN probabilities) and experiment / data storage. The PNN operates by defining a probability density function (PDF) for each data class based on the training set data and the optimized kernel width parameter. The PDF defines the boundaries for each data class. For classifying new events, the PDF is used to estimate the probability that the new pattern belongs to each data class. The output probability can be used as a level of confidence in the classification decision and can serve as a guide to reducing the false alarm rate. Most of the studies organized the data into three classes for analysis: fire, nonfire (background), and nuisance sources.

A new stepwise variable selection routine specifically designed for the PNN classifier was developed and used to select subsets of sensors. The code, called *VARSELPR*, used a straightforward implementation of forward selection using the sum of squared error from the PNN-cross validation algorithm as the criteria for the best sensor selection. The PNN variable selection routine allows the user to select the number of sensors to be included in the set and provides a mechanism to withhold sensors from consideration in the array.

Two approaches were used to analyze the processed and raw data sets. The processed data related most closely to the analyses in references (b and c), while the raw data analysis methods corresponded most closely to the studies described in reference (d). Both methods are given here for completeness. However, the raw data set methods are more relevant to real-time detection so they are used to determine the final candidate suites and to optimize the algorithms for real-time monitoring.

In the previous studies that investigated the laboratory data sets (references (b-d)), several sets of sensors were found to be useful for accurate fire detection and nuisance source rejection. Similar experiments were conducted to determine whether these same sets of sensors are important for the SHADWELL field data. To distinguish these experiments from ones where the laboratory data set is the training set and the SHADWELL field data is the prediction set, these experiments will be termed, *intra-set cross validation* because training and validation is done using sensor data from only one site. The term, *inter-set prediction* will be reserved to specify training on data from one site and prediction of another.

The last section of the report describes the experiments used to define two prototypes for testing on the SHADWELL in real time and the optimization of the algorithms for that application. In those experiments, the entire SHADWELL test was used in a playback mode.

4.1 Processed Data Analysis

Using the SHADWELL data, training and prediction sets were constructed at distinct times using the alarm times for the Simplex Photoelectric detector on Board A at the 11, 1.63, and 0.82 % obs/m sensitivity levels. A pattern or fingerprint of the event for each sensor was generated at these response times. The patterns were based on the average sensor readings for the last 10 data points and the rate of change (slope) from the last 25 values. For these experiments the training sets were taken from three points in time from each experiment. Thus, there are three patterns in the training set from each experiment resulting in a total of 90 pattern vectors. Background patterns were taken at two discrete times: two minutes after the data acquisition was initiated and a few seconds prior to ignition. For real fire events and nuisance sources, the pattern was computed using data collected at the given alarm times. For background events (mv00, mv03, mv13, mv26, and mv29) and nuisance sources that did not cause a false alarm, the third pattern was computed five minutes after source initiation or ten minutes after the start of data acquisition. For fire events that did not trigger an alarm at the most sensitive setting, the maximum reading of the Simplex Photoelectric detector on Board A was used to set the time at which the sensor fingerprint was evaluated. In all other cases, the alarm time from the next most sensitive level was used.

The initial tests used the SHADWELL field data as a prediction set for the laboratory training set at the 0.82% obs/m level. The data set consisted of 90 events, 65 backgrounds, 18 fires and 7 nuisance sources. The results are shown in Table 3a. These tests demonstrate the ability to train an algorithm with data from one location and predict data from another location under different environmental conditions, an inter-set prediction. There are some differences between the preprocessing of the laboratory data set (reference (b)) and the

SHADWELL data set. It is likely that these differences led to numerical instabilities in the PNN. The laboratory data was filtered using a Savitzky-Golay smoothing routine; this was not used for the SHADWELL data because the way it was implemented in the training set was not applicable to real-time processing that will occur later in the program. Due to differences in the data acquisition, the residential ionization sensor (RION) was not scaled in the same way, so there was a mismatch in the training and prediction sets. In addition, the rate of change was not used with the preprocessed data due to the differences in the methods used to calculate it.

Correct classification results range from 20-86%. The results are very low for some of the sensor combinations, particularly ones containing relative humidity (RH), O_2 and hydrogen (H_2) sensors. It appears that magnitudes are a problem for this application because the oxygen and humidity levels were very different between the two sites. When RH was in the sensor array, most of the experiments were classified as a fire. In addition, the hydrogen sensor changed its baseline response dramatically during the SHADWELL tests. The best performing results were for ION, PHOTO, and ODM sensor combinations. It is important to note that each of the sensors was converted to % obs/m, and thus have a form of background correction. Therefore, it was determined that background correction may be necessary.

For the background corrected studies, the background corrected data matrix used in univariate analysis described in reference (b) was used. The data set consisted of 82 fires and 38 nuisance sources. One minute of background was subtracted from the remainder of the data. It was necessary to treat the data as a two-class problem: fires and nuisance sources because all of the limited background data collected in those tests were used in the correction. The laboratory background corrected data matrix was studied using the leave-one-out cross-validation method (PNNCV) that sequentially trains all but one observation and predicts the one that was left out, an intra-set analysis approach. This procedure is repeated until all the observations or tests have been predicted. The results are shown in Table 3b.

Using the *VARSELPR*, CO_{4000}, RH, temperature (TC), ODM and PHOTO were found to be the best set of sensors. This set achieved 89% correct classification of the data set, correctly classifying 72 of the 82 fires and 35 of the 38 nuisances sources. The CO_{4000} sensor was not functioning during the SHADWELL test; therefore, the CO_{50} sensor was used in the prediction. When we change to CO_{50}, the performance of the training set is reduced to 83%, due to increased nuisance source alarms. The results are similar to those observed in the early work, the three-class approach including background responses for the sensors. When the best set (O_2, H_2S, RH, ION, and PHOTO) from reference (c) was used in this two-class approach, 18 events were missed, producing 85% correct classification. The missed events were 4% higher than in the previous work using a three-class approach (fire, nonfire, and nuisance sources), where the same set of sensors missed 13 events and correctly classified 92% of the data set. Other high performing sensor sets are shown in Table 3b.

The ability of the background corrected laboratory data to predict the SHADWELL data was investigated next. The prediction set, the SHADWELL data, was also background subtracted. In this case, the earliest background times described above were subtracted from

the responses at the alarm time, and the later background time. This reduced the data set by one third, 18 fires and 42 backgrounds/nuisance sources. Two identical sensor combinations were tested with both background correction and no correction. O_2, CO_{50}, ETHYL, ION and PHOTO produced similar overall results for both methods; however, more fires were missed with the background correction. The sensor array consisting of O_2, H_2S, RH, ION and PHOTO was greatly improved by background correction. While there was a big difference in relative humidity during the laboratory and SHADWELL tests, the change in relative humidity was similar.

Using the *VARSELPR*, RH, ETHYL, TC, RION, and PHOTO were found to be the best set of sensors for the SHADWELL data set. The intra-set cross validation results for this set achieved 92% correct classification and correctly classified 16 of the 18 fires and 39 of the 42 background and nuisances sources. The misclassified tests were flaming rags, welding, cutting steel, cigarette smoke, and flame applied to pipe insulation. These overall results are excellent and are similar to results achieved with the laboratory data set. However, prediction performance when the PNN is trained with the laboratory data is the goal for this study. Several sensor set combinations were investigated as shown in Table 3c. The set above provided the best fire detection, but the overall results were poor due to the high number of false alarms. When the RION sensor was removed, the results for both fire and nuisance sources improved. When ION was substituted in the above array for RION, the results improved to only 12 missed events; however, the correctly identified fires were reduced from 16 to 12. Different combinations of these sensors were investigated. The best overall performance using the SHADWELL data set as the prediction set was achieved with the ION sensor alone. The misclassified fires were flaming rags, welding, cutting steel, cigarette smoke, flame applied to pipe insulation, burning toast, and smoldering oily rags in a trash can. None of the sensor combinations were as strong as the intra-set results, suggesting that even with background subtraction there are significant differences between the laboratory and SHADWELL data sets that introduce calibration transfer issues. The preprocessing of the two data sets is different and may have contributed to the unsatisfactory prediction results.

Further tests with the processed data were abandoned due to the uncertainty of the results. The unsatisfactory results for some of the sensor arrays were likely due to the differences in the preprocessing approaches used for the laboratory and SHADWELL data sets. The remainder of the report describes the investigations using the raw data and treats both the laboratory and SHADWELL data sets identically.

Table 3. PNN Classification Results

Sensor Sets	Number Wrong	Number of Real Fires Correct	Number of False Alarms	Overall Percent Correct
(a) 0.82% (No Background Correction) SHADWELL	(90)	(18)	(72)	
CO_{50} ODM ION	20	5	7	78
Temp RH ODM ION PHOTO	40	10	32	56
O_2 H_2 Ethyl ION PHOTO	45	11	38	50
O_2 CO_{4000} H_2 ION PHOTO	46	11	40	50
O_2 CO_{50} Ethyl ION PHOTO	19	15	16	78
O_2 CO_{50} H_2S RH ION	72	18	72	20
O_2 H_2 Ethyl RION PHOTO	15	3	0	83
CO ION PHOTO	17	7	6	81
O_2 H_2S RH ION PHOTO	71	18	71	20
ION PHOTO	13	8	3	86
ODM ION PHOTO	13	8	3	86
CO_{50} NO ION PHOTO	18	4	4	80
(b) 0.82% (Background correction) Laboratory	(120)	(82)	(38)	
CO_{4000} RH TC ODM PHOTO	13	72	3	89
CO_{50} RH TC ODM PHOTO	20	73	11	83
O_2 CO_{4000} RH ION PHOTO	21	63	3	82
RH, Ethyl, TC, ION, PHOTO	20	69	7	83
O_2 H_2S RH ION PHOTO	18	72	8	85
(c) 0.82% (Background correction) SHADWELL	(60)	(18)	(42)	
RH, Ethyl, TC, RION, PHOTO (PNNCV)	5	16	3	92
RH, Ethyl, TC, RION, PHOTO	24	16	22	60
RH, Ethyl, TC, PHOTO	15	7	4	75
RH, Ethyl, TC, ION, PHOTO	12	12	6	80
TC, ION, PHOTO	7	15	4	88
ION, PHOTO	8	14	4	87
ION	7	15	4	88
RH, Ethyl	14	9	5	77
RH, Ethyl, PHOTO	15	11	8	75
CO_{50} RH TC ODM PHOTO ‘B’	15	7	4	75
O_2 CO_{50} Ethyl ION PHOTO	14	11	7	77
CO_{50} RH TC ODM PHOTO ‘A’	16	6	4	73
O_2 H_2S RH ION PHOTO	15	10	7	75

4.2 Raw Data Analysis

The laboratory and SHADWELL data sets were preprocessed in an identical manner for this study and all the methods are applicable to real time analysis. Several studies were conducted using the raw data. The electrochemical sensors in experiment MV-02 were prone to large spikes due to the Rf interference from the hand-held radios and interfered with the studies conducted using the raw data. Rather than attempt to filter the spurious data, patterns obtained from this experiment were removed from the raw data analysis. This reduced the size of the SHADWELL data set to 87 patterns.

Intra-Set Cross-Validation for the SHADWELL Field Test Data

In the previous study that investigated the laboratory data sets (reference (d)), several sets of sensors were found to be useful for accurate fire detection and nuisance source rejection. For these tests, sensor magnitude and slopes were considered. In reference (d), the magnitude of the sensor responses was sufficient for correct classification. Similar experiments were conducted to determine whether these same sets of sensors are important for the SHADWELL field data. Training and prediction sets were produced at the 11 and 0.82 % obs/m alarm levels as described earlier. An additional training set was constructed at the 0.82% level using a 10-point window for the slope. For each training set, *VARSELPR* was performed to select the optimal combination of sensors. Table 4 lists the fire detection and nuisance rejection accuracy of the three best sensor combinations. An additional experiment is listed in which only the slopes from window methods 4 and 8 (10 point and 25 point slopes) were available to the variable selection algorithm. For comparison, the performance of the four commercial Simplex detectors is given in Table 5.

To further elucidate the differences between the optimal sensor combinations for the SHADWELL and laboratory data sets, the linear correlation coefficient was computed between each variable and the correct classification of each pattern (1 = fire, 2 = not a fire). Table 6 lists the variables that had correlation coefficients greater than 0.5 (absolute value) for each training set.

Table 4. PNNCV Classification Performance for SHADWELL Field Test Data

Alarm Level	Win Size	Sensors	Missed Events	Number Correct		
				Fire	Nuis	Bkgd
11%	8	ΔPHOTO-B, ΔSION-B, ΔSION-A, ΔODM-B, ΔRION-B, PHOTO-A, ODM-A	MV14, MV15, MV20, MV23, MV24	12/17	7/7	63/63
0.82%	4	ΔSION-B, PHOTO-A, ΔH_2S, ΔRH-A, ΔCO_{50}-A, ΔRH-B, ΔPHOTO-B	MV6, MV9, MV14, MV16, MV22, MV25	16/17	2/7	63/63
0.82%	8	ΔRION-B, ΔPHOTO-A, RION-A, ΔRH-A, ΔRION-A, O_2-A, ΔCO_{50}-A	MV14, MV15, MV16, MV20, MV22	14/17	5/7	63/63
0.82 SLOPES ONLY	4/8	ΔSION-B(10), ΔSION-B(25), ΔPHOTO-B(10), ΔHCl(25), Δomega(25), ΔH_2S(25), ΔCO_{50}(25)	MV1, MV4, MV8, MV14, MV15, MV20, MV22, MV23, MV27	9/17	6/7	63/63

Table 5. Detection Performance for Commercial Systems at the SHADWELL Field Tests

Sensors	Setting	Number Correct		
		Fire	Nuis	Bkgd
PHOTO-A	11%	8/17	5/7	5/5
	1.63%	14/17	2/7	5/5
	0.82%	16/17	1/7	5/5
PHOTO-B	11%	8/17	6/7	5/5
	1.63%	13/17	2/7	5/5
	0.82%	17/17	1/7	5/5
SION-A	4.2%	13/17	4/7	5/5
	1.63%	13/17	3/7	5/5
	0.82%	14/17	3/7	5/5
SION-B	4.2%	14/17	4/7	5/5
	1.63%	14/17	4/7	5/5
	0.82%	14/17	3/7	5/5

Table 6. Ranked List of Linear Correlation Coefficients

Alarm Level	Ranked List of Sensors
11%	SION-B, SION-A, PHOTO-A, PHOTO-A, PHOTO-B, RION-B, RION-A, SION-B, O_2-A, PHOTO-B, CO_{50}-A, SION-A, RION-B
0.82% - 8	PHOTO-A, PHOTO-A, SION-B, SION-B, CO_2-B
0.82% - 4	(same as above plus RION-B)

Compared to the laboratory data in reference (d), the optimal sensor combinations for SHADWELL are much more heavily weighted toward the smoke detectors. This might be an artifact of having a larger amount of background data available for training. The gas sensors tend to have larger fluctuations, which increase the chances for false alarms on the background. The ionization and photoelectric sensors have stable baselines and lend themselves to excellent background rejection. The results in Table 5 clearly show that the smoke detectors have poor nuisance source rejection capabilities. When the sensitivity setting is low (11%) the Photoelectric detectors missed fires in order to get good nuisance rejection. At the most sensitive settings, most fires are detected, but at the price of poor nuisance immunity. However, even at the most sensitive settings no false alarms were detected in the background experiments.

The list of correlation coefficients and the variables chosen by *VARSELPR* suggests similar sensors to those chosen during the laboratory analysis (reference (d)). Smoke detectors continue to be important and the gas sensors that consistently find themselves being useful or having a high correlation with the correct classification include CO_2, O_2, CO_{50}, RH, and H_2S) and to a lesser extent (ETHYL and HCl).

Inter-Set Prediction

In these experiments, the laboratory data set was used as the training set and the SHADWELL data described above were used as the prediction set. The magnitude is an average of data points (5 or 10 total) and the slope is calculated over 10-25 points. The optimal number is unknown, so several different combinations were used in these studies. The various methods and selection codes are given below:

Selection Codes	1	=	magnitude(5)
	2	=	magnitude(10)
	3	=	magnitude(5) + slope(10)
	4	=	magnitude(10) + slope(10)
	5	=	magnitude(5) + slope(15)
	6	=	magnitude(10) + slope(15)
	7	=	magnitude(5) + slope(25)
	8	=	magnitude(10) + slope(25)

Initial experiments involved sensor combinations that were useful for intra-set prediction. Next, a new program was written, *VARSELPR*3, to perform *VARSELPR* using an external validation set to compute the sum of squared error. The prediction set (SHADWELL) classification performance is used as the criterion for selecting which sensors from the laboratory data (the training set) are most useful. While this method certainly biases the final model since the prediction data are used for PNN optimization, it does provide a rough estimate of what type of classification is possible with further data collection and algorithm enhancement.

Table 7 lists the results from inter-set prediction. The second column lists the parameters (alarm level and selection code) used for constructing the training and prediction sets. Column 3 gives the sensors used. The fourth column lists the PNNCV results using the training set (laboratory data). Columns 5 through 8 lists the prediction results using the laboratory data as the training set and the SHADWELL data as the prediction set. Columns 4 and 5 present the percent correct classifications for the intra-set cross validation of the laboratory data and the prediction of the SHADWELL data, respectively. Columns 6 to 8 show the number of events correctly classified per the total number of those events. The final column gives a set of comments pertaining to that experiment. In the comments section, a description of how that set of sensors was chosen and which board (A or B) was used to construct the SHADWELL prediction set. The best prediction found using an unbiased strategy are trials 5 and 6, while trial 10 is the best sensor combination found using a biased procedure.

The first two experiments used the best sensor combination (at the 0.82 alarm time and selection code #8) from our previous report. This combination uses several sensor magnitudes. As expected, this combination performs poorly in prediction due to differences in the background levels between laboratory and SHADWELL. This is a calibration transfer issue. The second set of experiments (rows 3-6 in Table 7) takes optimized sensor combination from our previous experiments, but uses slopes rather than magnitudes. This set performs much better and gives adequate performance compared to the commercial system at that sensitivity setting. The next set of experiments (rows 7-10) used the sensor combination chosen by *VARSELPR3* using the prediction set to guide the choice of sensors. The final set of experiments (rows 11 and 12) used sensor combination chosen by *VARSELPR*3 using both the prediction and CV error (sum of squared errors) as the criterion. This method seeks to find the sensor combination that performs well on both the laboratory and SHADWELL data sets.

Table 7. Inter-Set Prediction Results

Trial #	Level/ Win.	Sensors	% Correct		Number Correct			Comments
			PNNCV Lab data	Pred. Shad	Fire	Nuis	Bkgd	
1	0.82 8	CO_{50}, RH, PHOTO, O_2, ΔCO_2, ΔPHOTO	92.08	79.31	12/17	2/7	55/63	Best Combo from HAI; board A
2	0.82 8	CO_{50}, RH, PHOTO, O_2, ΔCO_2, ΔPHOTO	92.08	27.6	17/17	2/7	5/63	Best Combo from HAI; board B; high false alarm rate due to differences in O_2 magnitude
3	0.82 8	ΔPHOTO, ΔCO_2, ΔCO_{50}, ΔETHYL, ΔHCl	87.08	86.21	9/17	4/7	62/63	Slopes of best sensors from HAI; board A
4	0.82 8	ΔPHOTO, ΔCO_2, ΔCO_{50}, ΔETHYL, ΔHCl	87.08	85.05	10/17	2/7	62/63	Slopes of best sensors from HAI; board B
5	0.82 8	PHOTO, ΔCO_2, ΔO_2, ΔCO_{50}, ΔRH, ΔPHOTO	90.83	88.51	10/17	4/7	63/63	Slopes of best sensors from HAI: board A
6	0.82 8	PHOTO, ΔCO_2, ΔO_2, ΔCO_{50}, ΔRH, ΔPHOTO	90.83	90.80	13/17	3/7	63/63	Slopes of best sensors from HAI: board B
7	0.82 8	ΔPHOTO, SION, ΔO_2, ΔSION, PHOTO, ΔRH	85.42	90.80	13/17	3/7	63/63	VARSELPR3, PRED only; board A
8	0.82 8	ΔETHYL, SION, PHOTO, ΔPHOTO, ΔO_2, ΔH_2	86.67	93.10	14/17	4/7	63/63	VARSELPR3, PRED only; board B
9	0.82 4	ΔPHOTO, ETHYL, CO_2, ΔHCl, ΔNO	82.08	89.66	10/17	5/7	63/63	VARSELPR3; PRED only; board A
10	0.82 4	ΔSION, ΔPHOTO, PHOTO, RION, CO_2, CO_{50}	92.5	96.55	14/17	7/7	63/63	VARSELPR3; PRED only; board B
11	0.82 8	ΔPHOTO, ΔCO_2, PHOTO, HCl, RH, RION	94.17	87.36	8/17	5/7	63/63	VARSELPR3, Both PNNCV and PRED board A
12	0.82 8	26 22 10 44 15 24 ΔCO_{50}, PHOTO, NO, ΔPHOTO, RH, ΔCO_2	93.33	87.36	10/17	4/7	63/63	VARSELPR3, Both PNNCV and PRED board B

The results shown in Table 7 suggest that a combination of sensors can be used to predict both the laboratory and the SHADWELL data. The combination shown in trials 5 and 6 is selected in an unbiased manner and does well with both the laboratory PNNCV and the SHADWELL prediction. The best PNNCV results obtained for the laboratory data (reference

(d)) are around 92% (at the 0.82% level) and the combination of PHOTO, ΔCO_2, ΔO_2, ΔCO_{50}, ΔRH, ΔPHOTO gets over 90% of the patterns from the laboratory experiments correct. The best prediction results come, as expected, from the biased experiments trials 7-12. This represents the best that can possibly be done with laboratory data as the training set. Table 8 shows the results using *VARSELPR3* at the 1.63% obs/m alarm level. Little improvement is observed and the results are worse than the commercial systems at this alarm level. Ideally, the same sets of sensors would be chosen with the biased and unbiased methods. Ultimately the best sensor/algorithm combination will perform equally well on the laboratory and SHADWELL data sets. These results suggest that we are close to achieving this goal. However, the optimal sensor combinations were much different between Board A and B, which is disturbing.

Table 8. Inter-Set Prediction Results at 1.63% Alarm Level

Trial #	Level/ Win.	Sensors	% Correct		Number Correct			Comments
			PNNCV Lab	Pred. Shad	Fire	Nuis	Bkgd	
1	1.63 4	ΔPHOTO, NO, ΔRION, ΔSION, CO_2	86.67	90.80	11/17	5/7	63/63	VARSELPR3; PRED only; Board B
2	1.63 8	ΔETHYL, PHOTO, RION, ΔO_2, ΔOMEG, ΔPHOTO	91.25	89.66	13/17	3/7	62/63	VARSLEPR3; PRED only; Board B
3	1.63 4	ΔCO_{50}, PHOTO, CO_2, HCL, RH, ΔCO_2, ΔPHOTO	94.58	87.36	11/17	3/7	62/63	VARSELPR3; Both PNNCV and PRED; Board B
4	1.63 8	ΔCO_{50}, PHOTO, CO_2, HCL, RH, ΔCO_2, ΔPHOTO	94.17	89.66	11/17	4/7	63/63	VARSELPR3; Both PNNCV and PRED; Board B
5	1.63 4	ΔCO_{50}, PHOTO, CO_2, ΔPHOTO, ΔNO, HCl	93.33	89.66	12/17	3/7	63/63	VARSELPR3; Both PNNCV and PRED*; Board B
6	1.63 8	ΔCO_{50}, PHOTO, CO_2, HCl, RH, ΔPHOTO	92.92	86.21	11/17	2/7	63/63	VARSELPR3; Both PNNCV and PRED*; Board B

Background Subtraction and Conversion to Engineering Units

A common sensor preprocessing scheme involves background subtractions and conversion to engineering units. In this context, conversion to engineering units only pertains to the smoke detectors, as the raw data for the gas sensors were already in engineering units. Calibration models were used to convert the smoke detector readings to units of percent obscuration per meter. These calibration models are based on the calculation of I_0, which is essentially the average background reading. For both the gas sensors and the smoke detectors, the first 30 seconds of each test was used to determine the baseline reading. Data collected 30 seconds prior to source initiation were used to compute the background pattern for the laboratory training set.

The same types of experiments were performed on the background subtracted data sets as was done for the raw data sets. *VARSELPR3* was used to determine the optimal sensor combination for various window sizes and alarm levels. The results from these experiments are shown in Table 9. The best results are highlighted in bold text for each alarm level. The classification results are not much different from those in Tables 7 and 8. In addition to the 0.82 and 1.63% obs/m alarm levels, the 11% alarm level was investigated and very good PNN training and prediction performance was observed. There is a drop-off in fire detection and false alarm rate at the lower alarm levels.

The results are somewhat surprising since the background subtracted results are no better than the results from the raw data. Done properly, background subtraction effectively solves the sensor standardization issue since differences between the ambient background gas levels between different sites are subtracted out. Any remaining deviations from baseline can be attributed to the initiation of the fire or nuisance source or just the naturally occurring variations in the sensor output (either due to sensor instability or changes in the natural environment). Another interesting observation is that slope information is less critical for background subtracted data than it is for raw data. For raw data, the slopes were a critical ingredient toward successful sensor standardization (i.e., changes in sensor readings were consistent across sites even if the magnitude was not) and provided a convenient means of using the PNN to predict the SHADWELL test data. In these two studies, identical sensor combinations are not tested. However, the same methodology was used in each study to select the sensor combinations. The differences in the type of sensors selected suggest slope and background subtraction are equivalent. The next section investigates this issue again.

Table 9. Inter-Set Prediction Results from Background Subtraction/Conversion to Engineering Units

Level /Win.	Sensors	%Correct		Number Correct			Comments
		PNNCV Lab	Pred. Shad	Fire	Nuis	Bkgd	
0.82 4	**CO, ΔETHY, O2, PHOTO, ETHY, NO**	**92.5**	**89.65**	**13/17**	**3/7**	**62/63**	**VARSELPR3, Both PNNCV & PRED board A**
0.82 4	**ODM, RH, ΔPHOTO, ΔCO2, H2, CO2**	**89.17**	**91.95**	**10/17**	**7/7**	**63/63**	**VARSELPR3, Both PNNCV & PRED board B**
0.82 4	SION, ΔPHOTO, CO2, ΔOMEG, O2	86.25	89.65	13/17	2/7	63/63	VARSELPR3; PRED only; board A
0.82 4	SION, ΔODM, CO2, ΔPHOTO, ΔRH	84.58	91.95	12/17	5/7	63/63	VARSELPR3; PRED only; board B
1.63 4	**CO, O2, ΔCO, ETHY, PHOTO, NO**	**92.5**	**89.65**	**13/17**	**3/7**	**62/63**	**VARSELPR3, Both PNNCV & PRED board A**
1.63 4	**ODM, RH, O2, OMEG, ΔHCL**	**93.75**	**88.5**	**11/17**	**3/7**	**63/63**	**VARSELPR3, Both PNNCV & PRED board B**
1.63 4	SION, ΔODM, CO2, NO, ΔPHOTO	85.41	90.80	12/17	4/7	63/63	VARSELPR3; PRED only; board A
1.63 4	SION, ΔRION, CO2, ΔSION, ΔPHOTO, O2	83.75	94.25	13/17	6/7	63/63	VARSELPR3; PRED only; board B
11 4	**CO, O2, PHOTO, SION, ETHY**	**95**	**97.7**	**15/17**	**7/7**	**63/63**	**VARSELPR3, Both PNNCV & PRED board A**
11 4	**ODM, PHOTO, O2, ΔSION, H2S**	**96.25**	**96.55**	**13/17**	**7/7**	**63/63**	**VARSELPR3, Both PNNCV & PRED board B**
11 4	SION, ΔETHY, CO, ΔCO, O2, ETHY, PHOTO	95.42	96.55	14/17	7/7	63/63	VARSELPR3; PRED only; board A
11 4	RION, SION, ΔRION, O2, CO2, HCL	90.83	96.55	15/17	6/7	63/63	VARSELPR3; PRED only; board B

Inter-Set Prediction with Real-Time Playback

The experiments described above were performed at discrete times for both the training and prediction data set. A more relevant method of determining fire detection and nuisance source rejection performance involves real-time prediction of the sensor data. In reference (d), real-time PNN performance was assessed using the laboratory data set. In these experiments, real-time PNN performance is investigated by training the PNN on the laboratory data at discrete periods of time and processing the SHADWELL test data as though it were being collected in real time. These experiments will provide the most robust test, to date, of our multi-sensor array methodology since it demonstrates two important concepts: (1) using training data taken from site and predicting data collected at another; and (2) real-time analysis. The real-time playback experiments will also provide a means for determining response time to fires and the ability to reject nuisance sources and sensor changes due to changes in the ambient background level.

Thirty-one different combinations of sensors were chosen for these experiments and are listed in Table 10. The various sensor combinations were chosen based on the results from our previous work. The majority of the combinations involved only 5 sensors, however, some smaller sized arrays were also studied. In addition to sensor combination, several other variables were studied. The results shown in Tables 7-9 do not point to an obvious conclusion regarding the use of background subtracted or raw, so that option was studied as well. For earliest fire detection and highest nuisance source rejection, the optimal training set has not been determined. To study this, each sensor combination and preprocessing scheme was studied using PNN training sets constructed at the 11%, 1.63%, and 0.82% obs./m alarm levels of the Photoelectric system from the laboratory data. A fourth training set was constructed based on time at which five or more sensors have deviated 10 times the standard deviation of the background. The final consideration was the choice of using sensors from board 'A' or 'B'.

A total of 31 (sensor combinations) × 2 (preprocessing schemes, raw or background) × 4 training set conditions (deviation from baseline, 11, 1.63, or 0.82) × 2 Board selections ('A' or 'B') = 496 experiments were conducted. For each of these experiments, *VARSELPR3* was run to optimize the choices of slopes and magnitudes. The rationale behind this step is that some sensors have more informative slopes (change in sensor response as a function of time) than magnitudes and that the best mix of slopes and magnitudes is dependent upon the choice of the preprocessing method and training set composition. The best performing subset can be found in Table 11. The data were sorted according to highest nuisance source rejection capability.

Table 10. **Sensor Combination Studied in Real-Time Playback Experiments**

Combination #	Sensors
1	PHOTO SION CO O_2 ETHY
2	PHOTO SION CO CO_2 ETHY
3	PHOTO SION CO_2 O_2 CO
4	PHOTO SION CO_2 O2 ETHY
5	PHOTO SION RH OMEG CO
6	PHOTO SION RH OMEG CO_2
7	PHOTO SION RH OMEG O_2
8	PHOTO SION RH OMEG ETHY
9	PHOTO RH CO_2 O_2 CO
10	SION RH CO_2 O_2 CO
11	PHOTO ETHY CO_2 O_2 CO
12	SION ETHY CO_2 O_2 CO
13	RION ETHY CO_2 O_2 CO
14	RION OMEG RH CO CO_2
15	PHOTO SION RH CO O_2
16	PHOTO SION RION CO_2 CO
17	PHOTO SION RH CO_2 CO
18	PHOTO RION RH CO_2 CO
19	PHOTO H_2S CO CO_2 RH
20	PHOTO SION CO2 H_2S RH
21	PHOTO RION RH OMEG ETHY
22	PHOTO ODM RH OMEG CO
23	O_2 CO OMEG RH SION PHOTO
24	O_2 CO H_2 SION PHOTO
25	CO NO SION ODM
26	SION CO
27	PHOTO CO
28	PHOTO SION CO
29	PHOTO SION CO CO_2
30	SION CO CO_2
31	PHOTO CO CO_2

Table 11. The Best Performing Sensor Arrays for SHADWELL Prediction

Combination #	Alarm Time 1=0.82% 2=1.63% 3=11% 4=temporal	Preprocessing 1=bkgd 2=raw	Board A/B 1=A 2=B	Total Number of BKGD Tests Correct (29)	Total Number of Fire/Nuisance Tests Correct (29)	# of Fires Correct (17)	# of Nuisance Sources Correct (7)	# of BKGD Tests Correct (5)
20	**3**	**2**	**2**	**29**	**24**	**15**	**4**	**5**
19	**2**	**2**	**1**	**29**	**23**	**14**	**4**	**5**
17	**3**	**2**	**1**	**29**	**22**	**13**	**4**	**5**
25	**2**	**1**	**2**	**28**	**23**	**14**	**4**	**5**
30	**1**	**1**	**1**	**28**	**23**	**14**	**4**	**5**
19	**2**	**2**	**2**	**27**	**23**	**14**	**4**	**5**
20	**1**	**2**	**1**	**26**	**24**	**15**	**4**	**5**
5	**3**	**2**	**2**	**29**	**24**	**16**	**3**	**5**
20	**2**	**2**	**1**	**29**	**24**	**16**	**3**	**5**
6	3	2	1	29	23	15	3	5
6	3	2	2	29	23	15	3	5
16	3	2	2	29	23	15	3	5
17	3	2	2	29	23	15	3	5
19	1	2	2	29	23	15	3	5
19	3	1	2	29	23	15	3	5
19	3	2	1	29	23	15	3	5
20	3	2	1	29	23	15	3	5
26	3	1	1	29	23	15	3	5
26	3	2	1	29	23	15	3	5
27	3	2	1	29	23	15	3	5
28	1	2	1	29	23	15	3	5
28	3	1	1	29	23	15	3	5
28	3	1	2	29	23	15	3	5
29	3	2	2	29	23	15	3	5
25	3	1	2	29	22	14	3	5
26	3	1	2	29	22	14	3	5
26	3	2	2	29	22	14	3	5
28	3	2	1	29	22	14	3	5
28	3	2	2	29	22	14	3	5
30	3	2	2	29	22	14	3	5

The best performing sensor combinations are highlighted in bold text above and listed here.

5 PHOTO SION RH OMEG CO
17 PHOTO SION RH CO_2 CO
19 PHOTO H_2S CO CO_2 RH
20 PHOTO SION CO2 H_2S RH
25 CO NO SION ODM
30 SION CO CO_2

Sensor combinations 19 and 20 without background correction appear more than once with different board and alarm time selections. The deviation from baseline or temporal method to determine the training pattern was not present in any of the top performing combinations. All of the combinations include a smoke detector and sensors that have been identified in earlier studies as top performers. The overall correct classification results are similar to the intra-set PNN-CV described with both raw and processed approaches with 19 out of 24 fire/nuisance sources correctly processed. Based on the results above, combinations 19 and 20 would be selected. However, both of these combinations use the hydrogen sulfide sensor. The long term stability of this sensor is a concern because the calibration gas is unstable and expensive. Therefore, combinations 5 and 17 were selected due to the robust sensors in the arrays. The misclassified events for each of these arrays are listed in Table 12.

Table 12. Misclassified Events for Each Candidate Suite

PHOTO SION RH CO_2 CO	PHOTO SION RH OMEG CO
Burning Toast	Burning Toast
Cutting Steel	Cutting Steel
Cigarette Smoking	Cigarette Smoking
Smoldering cotton sheet, pillow, wool blanket, and mattress	Welding
Smoldering pillow in a pillow case	Smoldering pillow in a pillow case
TODCO Wallboard exposed to a flame	
Pipe insulation exposed to a flame	

5. CONCLUSIONS

This report describes an important step towards designing an early warning fire detection system. It investigates the ability of an algorithm trained on laboratory data to predict events at another location with different environmental parameters. Sensor combinations were identified that provide similar overall classification results between the intra-set studies and the inter-set study. Using the extensive playback investigation examining more than 400 variables, two candidate suites were selected for prototype development:

PHOTO SION RH OMEG CO
PHOTO SION RH CO_2 CO

The decision was difficult because there were several very good different combinations. Therefore, five additional sensors were selected to include in the future test, NO, H_2S, ETHYL, RION, and O_2. This will allow maximum flexibility in the future algorithm development. Much work remains in optimizing the algorithms for early fire detection for the best performance, however, the results continue to be encouraging.

The overall classification results of this study are not as good as in the previous work. While the multi-criteria detection system consistently performs better than the commercial photoelectric detector, the performance is similar to the ionization detector. The nuisance source rejection in this study is nearly identical. Due to the limited data set and lack of replicates it is difficult to access why this is the case. As time goes on and more shipboard fires/nuisance conditions are measured, the overall performance is expected to result in better predictions. However, observations made of the fire/nuisance tests in progress made it clear that the definition of nuisance source is a difficult decision. The burning toast experiment was extremely smoky and a small fire was produced in the toaster. Inclusion of items like this test in the training set will influence the predictions. If one looks at the results from reference (c) presented here in Tables 13 and 14, similar nuisance sources are missed. However, the earlier study had multiple replicates of each test and for all but cutting steel and grinding, only one replicate test was missed by the multi-criteria detection system.

In addition, there are differences in the experimental design of the laboratory and SHADWELL tests that generated the two data sets used here. The change in experimental design demands a new measure of success, and that should be time to alarm. In the fire/nuisance source tests completed in the laboratory, many of the small, incipient fires were not detected by the commercial fire detection systems. These systems are typically set at an alarm level (11-8% obs/m) because it provides the best nuisance source rejection and will detect a fire when it exceeds a given threshold. In the SHADWELL tests, the fires were larger in nature and were sustained long enough to produce an alarm by the commercial fire detection systems for most of the tests. Therefore, a direct comparison of correct classification as a measure of success is less useful here. The time to alarm would give more information about system performance and is more closely related to the goals of the program to produce an early warning fire detection system. The differences in these two data sets need careful examination and will be the subject of future tests and reports. As algorithm development proceeds, alternative measures of success will be used in optimizing the methods.

Table 13. Misclassified Events Using CO_{4000}, MICX, ODM and RION at the Photoelectric 0.82% Obs./m Alarm Level

Test ID	Scenario Type (Real/Nuisance)	Source Description
DCAS029	Real	Propane Bunsen burner
DCAS055*	Real	Smoldering Pillow, with pillow case
DCAS043	Real	TODCO wall panel
DCAS077	Nuisance	Burning Toast, one slice
DCAS083	Nuisance	Grinding cinder block
DCAS084	Nuisance	Grinding cinder block
DCAS085	Nuisance	Cutting steel with acetylene torch
DCAS087	Nuisance	Cutting steel with acetylene torch
DCAS088	Nuisance	Cutting steel with acetylene torch
DCAS101	Real	Smoldering electrical cable - LSTHOF-9
DCAS106	Real	Smoldering electrical cable - LSTPNW-1-1/2
DCAS107	Real	Smoldering electrical cable - LSTPNW-1-1/2
DCAS116	Real	Propane Meker burner
DCAS0132	Nuisance	Smoking 12 Cigarettes

* This test is one of four similar tests. Examination of the sensor responses indicates very small responses and a response pattern unlike the other replicates. In fact, this test was not a replicate at all because the heating rod was placed under the pillow rather than on top as with the other tests.

Table 14. Misclassified Events Using O_2, H_2S, RH, ION and PHOTO at the Photoelectric 1.63% Obs./m Alarm Level

Test ID	Scenario Type (Real/Nuisance)	Source Description
DCAS029	Real	Propane Bunsen Burner
DCAS055*	Real	Smoldering Pillow
DCAS074	Nuisance	Grinding Steel
DCAS088	Nuisance	Cutting steel with acetylene torch
DCAS110	Real	Igniting electrical cable with a torch - LSDSGU-14
DCAS116	Real	Propane Meker burner

*This test is one of four similar. Examination of the sensor responses indicates very small responses and a response pattern unlike the other replicates. In fact, this test was not a replicate at all because the heating rod was placed under the pillow rather than on top as with the other tests.

6. REFERENCES

(a) Carhart, H.W., Toomey, T.A., and Williams, F.W., "The ex-USS SHADWELL Full-scale Fire Research and Test Ship," NRL Memorandum Report 6074, revised January 20, 1988, reissued 1992.

(b) Gottuk, D.T., Hill, S.A, Schemel, C.F., Strehlen, B.D., Rose-Pehrsson, S.L., Shaffer, R.E., Tatem, P.A., and Williams, F.W., "Identification of Fire Signatures for Shipboard Multi-criteria Fire Detection Systems," NRL Memorandum Report 8386, June 18, 1999.

(c) Rose-Pehrsson, S.L., Shaffer, R.E., Hart, S.J, Williams, F.W., Gottuk, D.T., Hill, S.A, and Strehlen, B.D., "Multi-Criteria Fire Detection Systems Using a Probabilistic Neural Network," Sensors and Actuators, B, in press.

(d) Shaffer, R.E., Rose-Pehrsson, S.L., Williams, F.W., Barry, C., and Gottuk, D.T., "Development of an Early Warning Multi-criteria Fire Detection System: Analysis of Transient Fire Signatures Using a Probabilistic Neural Network," NRL Memorandum Report 8429, February 16, 2000.

(e) Rose-Pehrsson, S.L., Gottuk, D.T., Wong, J.T., Williams, F.W., Tatem, P.A., and Farley, J.P., "Test Plan for Multi-criteria Fire Detection System," NRL ltr 3901 Ser 6180/0517, 20 August 1999.

(f) Wong, J.T., Gottuk, D.T., Rose-Pehrsson, S.L., Shaffer, R.E., Tatem, P.A., and Williams, F.W., "Results of Multi-Criteria Fire Detection Systems Tests - Part I: Test Documentation and Results of Fire Detectors," NRL Memorandum Report XXXX, 2000.

(g) Shaffer, R., Rose-Pehrsson, S.L., and McGill, R.A., "Probabilistic Neural Networks for Chemical Sensor Array Pattern Recognition: Comparison Studies, Improvements and Automated Outlier Rejection", NRL/FR/6110-98-9879, March 10, 1998.